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Ashabul Kahfi Serious Game with Adaptive Recommendation System Based on Knowledge-Based Filtering and MULTIMOORA for Islamic Education

Yuniar Setyo Marandy[1], Fresy Nugroho[2], Ririen Kusumawati[3]

UIN Maulana Malik Ibrahim Malang, Kota Malang, Jawa Timur, Indonesia

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Corresponding Author
Yuniar Setyo Marandy
UIN Maulana Malik Ibrahim Malang
240605210025@student.uin-malang.ac.id

ABSTRACT

This study aims to develop a serious game based on the story of Ashabul Kahfi using a difficulty level recommendation system based on Knowledge-Based Filtering (KBF) and the MULTIMOORA method. This game is designed for elementary school students in the context of Islamic religious education, instilling moral and spiritual values through the narrative of the story of Ashabul Kahfi. The difficulty level in the game is adjusted to the player's profile based on age, experience, and preferences obtained through a questionnaire. The MULTIMOORA method is applied to process questionnaire data and provide adaptive and personalized difficulty level recommendations. The results of the study show that the application of this recommendation system is able to increase student learning motivation and learning effectiveness by providing challenges that are appropriate to each player's abilities. Thus, this study contributes to the development of adaptive and effective game-based learning media, particularly in improving the understanding of religious values among students.

INTRODUCTION

The development of information and communication technology (ICT) has had a significant impact on various fields, one of which is education. One innovation that is currently developing in the world of education is the use of serious games, which are not only intended for entertainment but also for educational purposes [1], [2]. The use of serious games as a learning medium has been proven effective in increasing student motivation, engagement, and understanding, especially among the generation that has grown up with digital technology [1], [2]. In the context of Islamic education, such as teaching moral and spiritual values, serious games also have great potential to provide a more enjoyable and interactive learning experience [3], [4]. Recent research even confirms that adaptive serious game frameworks can increase engagement and learning effectiveness across educational contexts [2], [5].

One of the challenges in developing serious games is determining the level of difficulty that suits the abilities and needs of the players. An inappropriate level of difficulty can reduce the effectiveness of learning. A level that is too easy can cause boredom, while one that is too difficult can cause frustration and decrease motivation to learn [6]. Therefore, it is important to develop a system that can adaptively adjust the level of difficulty so that the learning experience remains optimal and interesting for students. Recommendation systems based on KBF and the Multi-Objective Optimization on the basis of Ratio Analysis (MULTIMOORA) method are appropriate approaches to address this issue, as both can provide more personalized and adaptive recommendations based on user characteristics [7], [8].

In game-based education studies, adjusting the level of difficulty according to the player's profile is important to ensure an effective and enjoyable learning experience. Several recent studies show that the Knowledge-Based Filtering method can be used to provide content or challenge recommendations based on explicit user data, such as age, experience, and preferences [9]. In addition, the MULTIMOORA method of has been proven effective in multi-criteria decision making involving various interacting factors [10]. These two methods can be integrated to provide difficulty level recommendations that match the abilities and preferences of players in serious games [11].

Adaptive recommendation methods play an important role in online learning systems and educational games, as they are able to adjust the level of challenge to user characteristics such as age, experience, and learning preferences. One widely used approach is KBF, which is a recommendation system that utilizes domain knowledge and user profiles to determine the suitability between student characteristics and the learning content provided [12]. Research shows that AI-based adaptive learning systems can significantly improve student academic performance [13], [14]. This hybrid KBF and MULTIMOORA approach makes it possible to generate suitability scores and difficulty level decisions mathematically and objectively, overcoming the limitations of each method so that the adaptation of the learning experience becomes more accurate [15], [16].

The integration of adaptive technology in Islamic education is still limited, despite its enormous potential in improving understanding of Islamic values [17]. This study fills this gap by developing the Ashabul Kahfi serious game, which integrates the KBF-MULTIMOORA hybrid recommendation system to provide a personalized and adaptive learning experience [18], [19], [20].

METHODS

This study uses a Research and Development (R&D) approach with the aim of developing the Ashabul Kahfi serious game equipped with a difficulty level recommendation system based on KBF and the MULTIMOORA method. The R&D approach was chosen because the focus of this study is to produce a product that can be directly applied in Islamic education for elementary school students. The research process followed the ADDIE development model, which consists of five stages: Analysis, Design, Development, Implementation, and Evaluation [21], [22].

1. Analysis: An analysis was conducted on learning needs and user characteristics, namely elementary school students. This included understanding the learning material on moral values in the story of Ashabul Kahfi and student preferences regarding the difficulty level of the game.
2. Design: The design focused on designing the game and difficulty level recommendation system using the KBF and MULTIMOORA methods, which were tailored to the students' abilities and preferences. The adaptive recommendation system was designed to dynamically adjust game difficulty using a hybrid KBF-MULTIMOORA mechanism. The KBF layer maps each player's profile vector:

$$P_{\mathrm{i}} = [\, a_{\mathrm{i}} , g_{\mathrm{i}} , e_{\mathrm{i}} , p_{\mathrm{i}} , r_{\mathrm{i}} \,]$$

representing age, grade level, gaming experience, difficulty preference, and learning response against predefined knowledge rules representing ideal profiles for each difficulty category (Easy, Moderate, Difficult). Each attribute is normalized within a range of 0-1 using the Min-Max normalization formula:

$$x'_{\mathrm{i}k} = (x_{\mathrm{i}k} - x_k\text{\^{}}min) \,/\, (x_k\text{\^{}}max - x_k\text{\^{}}min)$$

The similarity between the player's profile and the ideal profile is computed using a weighted Euclidean distance:

$$S_{\mathrm{ij}} = 1 - \sqrt{}(\Sigma_{\mathrm{k=1}}{}^{\mathrm{n}} \; w_{\mathrm{k}} \, (x'_{\mathrm{ik}} - K'_{\mathrm{jk}})^2)$$

The KBF output produces an initial suitability score that serves as input for the MULTIMOORA module, which optimizes the decision-making process across multiple criteria, such as learning engagement and preference alignment. MULTIMOORA applies three integrated approaches-Ratio System, Reference Point, and Full Multiplicative Form-to calculate a comprehensive ranking of alternatives. The final difficulty level recommendation is obtained using the decision rule:

$$Level(P_i) = argmax_j\,(S_{ij})$$

This ensures that each student receives a personalized challenge level-Easy, Moderate, or Difficult-based on an objective and adaptive assessment of their learning characteristics. The overall design thus combines narrative-based engagement with mathematically grounded adaptivity, creating a balanced educational experience that aligns with cognitive development and motivational principles.

3. Development: The designed game will be developed using the Unity platform, and the recommendation system will be implemented to adjust the game's difficulty level based on data obtained from questionnaires filled out by students. The total performance value of each alternative is calculated by summing the normalized results of each criterion multiplied by its weight:

$$y_i = \sum_{j=1}^{n} w_j \cdot x_{ij}$$

The Reference Point Approach compares each alternative to an ideal reference point that represents the maximum value of each criterion. The distance of each alternative from the ideal point is calculated using the formula:

$$d_i = \max_j \left| r_j - x_{ij} \right|$$

The Full Multiplicative Form approach calculates the performance value of each alternative by multiplying all benefit criteria and dividing it by the product of all *cost* criteria:

$$FMF_i = (\textstyle\prod_{(k=1)}^{m} (x'_{ik})\ ^\wedge w_k) \,/\, (\textstyle\prod_{(k=m+1)}^{n} (x'_{ik})\ ^\wedge w_k)$$

The three methods are combined to obtain consistent and comprehensive results. The final ranking is obtained by aggregating the results of the three methods using *the majority rule* or average ranking method.

$$r_i = (rankRS_i + rankRP_i + rankFMF_i) / 3$$

The integrated application of the three approaches in the MULTIMOORA method (Ratio System, Reference Point, and Full Multiplicative Form) produces a more comprehensive and reliable recommendation system than using only one approach.

4. Implementation: The completed game will be tested on students at State Elementary School 01 Pakisaji in Malang Regency. Data will be collected through observation, questionnaires, and pretest and posttest tests. This study involved a total of 40 students divided into two groups: 20 in the experimental group and 20 in the control group. The sample was selected using a purposive sampling technique based on the students' age and grade level (grades IV-VI) at SDN 01 Pakisaji, Malang Regency. The experimental group used the serious game Ashabul Kahfi, developed with an adaptive recommendation system based on KBF-MULTIMOORA, while the control group followed conventional learning without games. The research instruments included a learning motivation questionnaire, a student interaction observation sheet, and a moral understanding test (pretest and posttest). Prior to use, the questionnaire and test instruments were validated through content validity by three experts and reliability testing using a pilot test on 10 students outside the study sample. The pilot test results showed that the instrument items met the criteria for validity and reliability, with a reliability coefficient value of >0.70, making them suitable for use in the main study.
5. Evaluation: The results of the game's implementation will be evaluated by looking at its impact on students' learning motivation and understanding of the moral values contained in the story of Ashabul Kahfi. The evaluation will be carried out by analyzing data obtained from questionnaires, pre-tests, post-tests, and observations to determine the effectiveness of the game in learning.

The subjects of this study were students in grades IV to VI at Pakisaji State Elementary

School 01, who were selected using purposive sampling. This selection was made by considering the students' age and experience in playing educational games. Data was collected through questionnaires that measured students' preference for difficulty levels and their motivation for learning, which was then used to tailor the game to each student's characteristics. Other instruments used to collect data were pre-tests and post-tests to measure students' understanding of the moral values of the Ashabul Kahfi story before and after playing the game. In addition, observations were made to record students' interactions with the game and their responses to the difficulty levels suggested by the recommendation system. The participants were divided into two groups: the experimental group, which would use the game, and the control group, which would use conventional learning methods. Each student in the experimental group will play the game for 4 sessions, each lasting 30 minutes, while the control group will participate in lecture-based learning activities. The control class consists of 20 students and the experimental class consists of 20 students.

Data analysis uses descriptive statistical analysis to measure student motivation and preferences based on completed questionnaires. Pretest and posttest data will be analyzed using paired t-tests to determine whether there are significant changes in student understanding after using the game. Observation data will be analyzed qualitatively to understand how students interact with the game and how difficulty level recommendations affect their learning experience [23], [24].

RESULTS AND DISCUSSION

This study aims to develop the Ashabul Kahfi serious game with a difficulty level recommendation system based on KBF and the MULTIMOORA method. The game was developed with narrative elements representing the story of Ashabul Kahfi, integrated with gameplay mechanisms that encourage students to interact with the story through challenges involving avoiding Roman army patrols and collecting coins [25], [26].

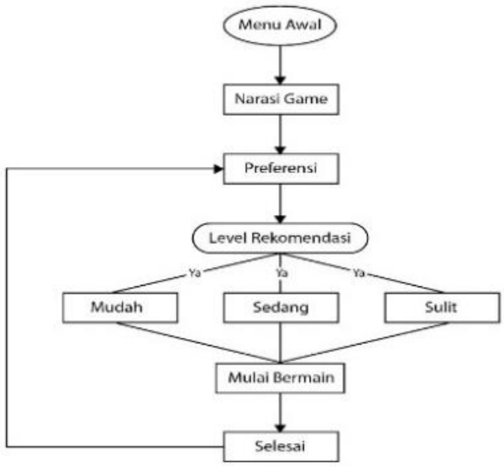

Figure 1. Gameflow of the Ashabul Kahfi Serious Game

The game design consists of two stages: creating the game design and creating the MULTIMOORA system design. The type of game chosen uses a survival game concept where players are required to avoid and hide from patrolling Roman soldiers and collect coins that appear randomly in the game area to earn points without any time limit. The selection of characters, backgrounds, and game assets uses visuals inspired by the story of Ashabul Kahfi in accordance with the concept of Islamic religious education in elementary school in the Ashabul Kahfi subject matter.

Designing a MULTIMOORA-based Knowledge-Based Filtering recommendation system to adjust the difficulty level based on the age and preferences of players selected in a questionnaire at the beginning of the game. The questionnaire used to determine player references is as follows:

Table 1. Questionnaire List

Questionnaire Questions	Theoretical Dimension	Reference
Age	Cognitive development	[27
Grade	Curriculum & User Profile	[28]
Game Playing Frequency	Familiarity & Self-Efficacy	[29
Game Type Preferences	Player type & learning interest	[30
Game Difficulty Response	Flow & Self-Regulation	[31], [32]

After collecting questionnaire data, the recommendation system will process the KBF system, which can map age and difficulty preferences to determine the appropriate level. MULTIMOORA will then integrate this data with other factors, such as educational value and game duration, to provide more comprehensive recommendations [33], [34].

The following are the steps in using the MULTIMOORA method:

1. Initial Data Formation (KBF Input): The initial stage is carried out by collecting player characteristic data through a knowledge-based questionnaire. Each player is asked to answer five questions covering age, class, playing experience, difficulty preferences, and response to the game. Each answer is converted into a numerical score on a scale of 1 (low), 2 (medium), and 3 (high) to form a player characteristic vector. This data forms the basis for the formation of a decision matrix in the MULTIMOORA process [35], [36].
2. Formation of the Decision Matrix: The KBF results data are represented in the form of a decision matrix, where each element represents the numerical value of the questionnaire results for specific alternatives and criteria.
3. Value Normalization (Min-Max Normalization): To equalize the scale between criteria, normalization is performed using the Min-Max formula. This process produces standardized values in the range of 0-1 so that each criterion has a balanced contribution in the decision-making process.
4. Total Score Calculation (Ratio System): The total score in the Ratio System method is calculated by adding up the normalized criteria values, each of which can be given a weight according to its level of importance. If all criteria are considered to have the same level of importance (equal weighting), then the total score can be calculated as the average of the normalized values.
5. Reference Point Approach (RP) Calculation: The second stage is the Reference Point approach, which aims to measure the distance of each alternative from the maximum ideal point for each criterion.
6. Full Multiplicative Form (FMF) Calculation: The third stage is the Full Multiplicative Form approach, which considers the ratio between the multiplication results of all benefit and cost criteria for each alternative [37], [38].
7. Integration and Determination of Final Recommendations: The three calculation results (RS, RP, and FMF) are then sorted and combined using the majority rule or average rank aggregation method to obtain a more objective final ranking. The alternative with the best average ranking is determined as the recommended difficulty level for players [39], [40]. "Game level recommendation map: Market (Easy) / Forest (Medium) / Desert (Difficult)." This integrated approach between KBF and MULTIMOORA ensures that the difficulty level recommendations provided are adaptive, personalized, and objective based on the individual profiles and preferences of students [41], [42].

Figure 2. Excerpt from the Level Recommendation Script with KBF and MULTIMOORA

The visual design of the game uses backgrounds similar to those in the stories of the Quran in the Middle East, including desert landscapes, caves where the young men took refuge from the Roman army, and a market where they realized they had awakened from their long sleep. At the beginning of the game, players will be presented with a comic-style narrative that reveals the background story of Ashabul Kahfi, which tells the journey of a group of young men who were forced to flee from persecution. Static illustrations will be used for to depict the tension and difficulties faced by these young men. Through these visuals, players will immediately feel their despair while understanding that they must survive with unwavering faith amid the pressures of the outside world.

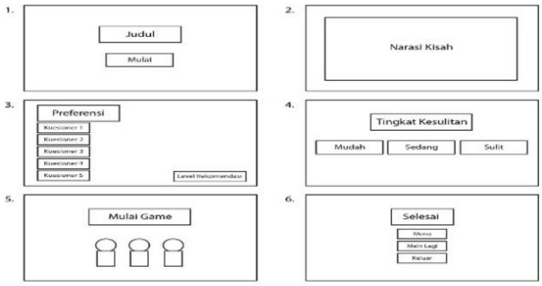

Figure 3. Storyboard for the Ashabul Kahfi Serious Game

The game was created using unity software, while the graphic elements were created using Adobe Illustrator and Adobe Photoshop software.

Figure 4. Display of the Ashabul Kahfi Serious Game

After the game was developed, it was tested at State Elementary School 01 Pakisaji in Malang Regency. During the trial, data was collected through direct observation, questionnaires, as well as pre-tests and post-tests to measure students' understanding of the moral values contained in the story of Ashabul Kahfi. Based on 40 respondent data collected through questionnaires, a general profile of students was obtained, which became the basis for the KBF recommendation system to determine the level of difficulty of the game.

The recommendation system in this study uses a KBF approach that maps user characteristics (students) into a game difficulty level suitability profile. KBF calculates the similarity value between the player's profile and the knowledge model that has been defined based on logical rules (rule-based) or certain mathematical functions [43], [44].

In this study, each student is represented by a characteristic vector, namely:

Table 2. Age and Grade Distribution Data

Age (Years)	Number of Students	Percentage	Dominant Grade
9	8 students	20	IV
10	10 students	25	IV-V

Age (Years)	Number of Students	Percentage	Dominant Grade
11	10 students	25	V-VI
12	12 students	30	VI

The majority of respondents were aged 10 to 12 years old, a group that already has intermediate cognitive abilities, making them suitable for educational games with adaptive difficulty levels.

Table 3. Game Playing Experience Data

Level of Experience	Number of Students	Percentage	Characteristics
Beginner	16 students	40	New to educational games, requires basic guidance
Intermediate	13 students	32.5	Already familiar with simple game mechanics
Proficient	11 students	27.5	Highly experienced and quick to adapt to complex gameplay

Most students are in the beginner category (40%), indicating the need for an easy initial difficulty level so that they can understand the game mechanics.

Table 4. Difficulty Level Preference Data

Preference Choice	Number of Students	Percentage	Tendency
Easy	20 students	50	Students are more comfortable with light challenges
Moderate	13 students	32.5	The majority prefer a moderate level of difficulty
Difficult	7 students	17.5	A small number prefer high challenges

A total of 50% of students chose easy difficulty, indicating that some students prefer easy difficulty levels.

Table 5. Learning Response Data

Response Type	Number of Students	Percentage	Description
Passive	13 students	32.5	Requires a more interactive approach
Sufficient	15 students	37.5	Shows moderate engagement during play
Active	12 students	30	Very enthusiastic and motivated during play

The MULTIMOORA method consists of three main approaches, namely the Ratio System, Reference Point Approach, and Full Multiplicative Form, which are used in an integrated manner to produce a more objective final ranking. Input data is converted into numerical values and normalized using Min Max, then the total score is calculated (Ratio System) [45], [46].

Table 6. MULTIMOORA Rating Scale

Total Score Range	Difficulty Recommendation
$0.00 \le$ score ≤ 0.60	Easy
$0.61 \le$ score ≤ 0.90	Moderate
$0.91 \le$ score ≤ 1.00	Difficult

Based on data from 40 respondents from Pakisaji 01 Public Elementary School, the KBF and MULTIMOORA-based recommendation systems produced the following difficulty level distribution:

Table 7. Recommendation System Analysis Results Data

No	Age	Grade	Experience	Preference	Response	RS Score	RP Dist	FMF Utility	Rank RS	RP Rank	FMF Rank	Average Rank	Recommendation (Integration)
1	10	4	Beginner	Easy	Active	0.48	0.70	0.40	28	27	29	28.0	Easy
2	11	5	Moderate	Moderate	Fair	0.62	0.49	0.56	15	12	14	13.7	Moderate
3	9	4	Beginner	Easy	Passive	0.27	0.83	0.22	38	36	39	37.7	Easy
4	10	5	Moderate	Moderate	Fair	0.62	0.49	0.56	14	12	13	13.0	Moderate
5	12	6	Proficient	Difficult	Active	0.91	0.08	0.85	1	1	1	1.0	Difficult
6	11	5	Moderate	Moderate	Fair	0.62	0.49	0.56	13	12	12	12.3	Moderate
7	10	4	Beginner	Easy	Passive	0.27	0.83	0.22	37	36	38	37.0	Easy
8	9	4	Beginner	Easy	Passive	0.27	0.83	0.22	39	36	39	38.0	Easy
9	11	5	Moderate	Moderate	Fair	0.62	0.49	0.56	12	12	12	12.0	Moderate
10	12	6	Proficient	Difficult	Active	0.91	0.08	0.85	2	1	1	1.3	Difficult
...	...	...	...	...	...	...	...	...	...	...	...	...	...
30	10	5	Moderate	Moderate	Fair	0.62	0.49	0.56	4	12	11	9.0	Moderate
31	9	4	Beginner	Easy	Fair	0.33	0.75	0.29	29	33	30	30.7	Easy
32	10	5	Beginner	Intermediate	Active	0.53	0.60	0.47	20	21	21	20.7	Moderate
33	10	5	Medium	Moderate	Fair	0.62	0.49	0.56	3	12	10	8.3	Moderate
34	9	4	Beginner	Easy	Fair	0.33	0.75	0.29	27	33	30	30.0	Easy
35	11	6	Proficient	Easy	Active	0.73	0.36	0.65	17	9	16	14.0	Moderate
36	9	4	Proficient	Easy	Passive	0.40	0.66	0.35	25	25	26	25.3	Easy
37	9	4	Proficient	Difficult	Active	0.62	0.49	0.56	16	12	14	14.0	Moderate
38	9	4	Proficient	Easy	Fair	0.40	0.66	0.35	24	25	25	24.7	Easy
39	9	4	Moderate	Easy	Active	0.44	0.62	0.39	22	23	24	23.0	Easy
40	11	6	Beginner	Easy	Passive	0.47	0.63	0.39	21	24	23	22.7	Easy

Most of the 15 students (37.5%) received recommendations at a moderate difficulty level, indicating that the system can adjust challenges to the abilities of the majority of players. Analysis of the observation results also showed that 80% of students felt that the difficulty level was appropriate for their abilities and felt more motivated to learn after playing the game [47], [48].

The trial results showed that students who were given a difficulty level tailored to their abilities showed higher levels of engagement, with more students feeling motivated to continue playing the game. About 80% of students reported that they felt more motivated to learn after playing the game, especially at medium and difficult levels of difficulty. The results of the observation also showed that students interacted more actively with the game when the challenges were adjusted to their abilities, without feeling frustrated or bored [49], [50].

Table 8. Student Motivation Data After Playing the Game

Difficulty Level	Number of Students	Motivated Students	Percentage Motivated	Description
Easy	14 students	9 students	64	The challenges are considered easy, and some students get bored quickly
Moderate	18 students	16 students	89	The level of difficulty is appropriate for the majority of students' abilities, sparking curiosity and encouraging questions.
Difficult	8 students	7 students	88	Proficient students feel challenged and more focused on understanding moral values
Total / Average	40 students	32 students	80	Overall, students showed an increase in learning motivation after playing

This data provides an overview of students' experiences in facing difficulty levels tailored to their abilities. The questionnaire results show how relevant and effective the recommendation system is in maintaining student engagement and motivation during the game. If the majority of students report that the game's difficulty level is appropriate for their abilities and provides motivating challenges, then the system can be considered effective in creating an adaptive and personalized gaming experience [51], [52].

Direct observation of student interactions with the game also provides deeper insight into how students adapt to the game mechanics and challenges presented. These observation results are integrated with quantitative data to provide a comprehensive picture of the effectiveness of serious games in achieving educational goals. If the analysis shows a significant increase in students' moral understanding and positive feedback on the gaming experience, it can be concluded that the game is effective in conveying moral and spiritual values to students [53], [54].

Measurements of moral values understanding through pretest and posttest also showed a significant increase. The results of the paired t-test analysis between the pretest and posttest scores show a significant difference ($p < 0.05$), indicating that after playing the game, students showed a significant increase in their understanding of the moral values contained in the story of Ashabul Kahfi [55], [56].

Table 9. Students' Pretest and Posttest Scores (N=40)

No	Pretest Score	Posttest Score	Increase (%)
1	55	72	30.9
2	60	78	30.0
3	50	65	30.0
4	58	76	31.0
5	62	80	29.0
6	59	76	28.8
7	56	73	30.4
8	61	79	29.5
9	63	81	28.6
10	57	74	29.8
...	...	...	...
31	62	81	30.6
32	55	72	30.9

No	Pretest Score	Posttest Score	Increase (%)
33	57	75	31.6
34	60	78	30.0
35	58	76	31.0
36	59	77	30.5
37	61	79	29.5
38	63	82	30.2
39	64	83	29.7
40	54	71	31.5

Based on the results of the pretest and posttest of 40 students, the average pretest score was 58.2 and the average posttest score was 75.7. Thus, there was an average increase of 30.1% after using the Ashabul Kahfi serious game. The paired t-test results showed a significance value of $p < 0.05$, which means that there was a significant difference between before and after the treatment. These findings confirm that the application of an adaptive recommendation system based on KBF and the MULTIMOORA method effectively improves students' understanding of moral values [57], [58]. This improvement also reinforces the observation that most students feel more motivated and active during the learning process [59], [60].

CONCLUSION AND RECOMMENDATIONS

This study successfully developed the Ashabul Kahfi serious game equipped with with an adaptive recommendation system based on KBF and the MULTIMOORA method to improve Islamic education among elementary school students. The results show that the application of this recommendation system is effective in adjusting the game's difficulty level to students' abilities and preferences, thereby increasing their motivation and understanding of the learning material. The developed game is able to provide challenges that are appropriate to each student's abilities, which in turn increases their involvement in the learning process. Overall, the development of this game has made a positive contribution to the use of technology in Islamic education, particularly in creating an adaptive and engaging learning experience for students.

Although this study shows positive results, some students still have difficulty following the sensitivity of the player character's movements in the game. Therefore, further research is recommended to simplify character movement in the game so that it is easier for all students to control. In addition, the development of similar educational games should consider more varied content and interactions to increase student engagement more comprehensively. This research can also be expanded by involving more schools and age groups to obtain more representative results. Further development of recommendation systems, such as the use of AI technology to adjust the difficulty level in real-time, could be the next step to improve the effectiveness of learning through games.

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